RESEARCH PAPER

Pillsure: A Dual-Modal Spectral And Imaging Framework For Tablet Authentication

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Abstract
Nowadays, a large part of our population depends on daily medication, which makes the quality, authenticity, and safety of tablets be three major criteria to be met. Nevertheless, there are cases when tablets are discovered out of the blister pack, having faded imprints, looking old, or even have slightly changed their shape. Then, hardly can their legitimacy be confirmed and the only sure way becomes a laboratory test, which takes a lot of time and is not at hand immediately. This work proposes a compact and portable pill verification device based on a dual-modal decision pipeline. The system integrates spectroscopic analysis using a micro NIR spectrometer and imaging analysis using a compact CMOS camera equipped with a macro microlens. The spectral data captures the chemical fingerprint of the tablet, while the imaging module analyzes its visual and structural characteristics. The collected data from both modalities are processed using a trained machine learning classifier for spectral verification and a convolutional neural network (CNN) for image-based validation. The final authentication decision is obtained through decision-level data fusion of both outputs. In addition, the proposed system can very quickly and easily identify pills in a non, destructive and portable manner, thus providing a convenient and readily available alternative to the lengthy and costly standard laboratory, based drug verification that is not easily accessible.

Keywords*: spectroscopic analysis, microlens imaging, machine learning, rapid and non-destructive tablet verification.*
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I. Introduction

The realness and standard of pharmaceutical tablets are a major factor for the safety of patients and their recovery. Still, fake, outdated, and broken, down drugs are reportedly the major cause of the problem, especially when people get tablets without original packaging or proper traceability. Because tablets that look alike may have very different chemical compositions or surface conditions, users or pharmacists manually checking them visually can be quite unreliable.

The present methods for drug verification mainly concentrate on laboratory analytical techniques like chromatography and sophisticated spectroscopy. Even though such methods can be very precise, they are also costly, run over a long time, and need special facilities and trained staff which totally excludes them from being used for regular, emergency, and local verifications. So, there is a big gap between accurate laboratory testing and the requirement for a quick and easily available pill verification in everyday situations.

II. Related Works

Below, we review key prior works in relevant domains.

A. Laboratory, Based Drug Authentication Methods

Previous research has mostly been based on using advanced laboratory, grade spectroscopic instruments for drug analysis like high, performance liquid chromatography (HPLC), mass spectrometry, and Fourier transform infrared (FTIR) spectroscopy [1], [2]. These methods take an accurate measurement of a drug's chemical makeup and purity and are the standard procedures approved by the regulatory authorities. Still, such methods necessitate costly equipment, experts' knowledge, and specially equipped laboratory facilities, and thus they are not practical for quick or on, the, spot drug verification [3].

Technology in miniaturized spectroscopic sensors, embedded imaging systems, and machine learning has paved the way for new drug examination approaches. Spectroscopic sensing can identify chemical consistency non, destructively by using characteristic light, matter interactions, and micro, lens imaging can reveal surface features that are likely to be contamination, degradation, or physical defects. Nevertheless, the majority of the present solutions depend on one single mode of analysis which can hardly be sufficient for practical reliable operation.
This work addresses this limitation by proposing 'PillSure; a compact, portable pill verification system that integrates spectral analysis for chemical consistency with micro-lens imaging for surface contamination detection, supported by machine models are to enable consistent and objective classification of tablet characteristics.' The objective is not to replace laboratory testing, but to provide a fast, affordable, and on-site screening tool that improves decision-making and reduces dependence on subjective visual inspection.

B. Mobile Application and Camera, Based Verification Systems

Some mobile, based solutions focus only on the visual aspect that is captured through smartphone cameras, hence compromising reliability when the surface is degraded. Such systems generally use image processing along with deep learning models for pill recognition [4], [5]. On the one hand, these methods are less expensive and straightforward to release; however, they are unable to check drug authenticity chemically because counterfeit medicines can have their respective tablets' visual appearance closely imitated. Furthermore, camera, based systems have quite a few limitations as they are very dependent on the lighting conditions, camera quality, and surface wear, therefore, camera, based systems generate less trustworthy

results. Key downside: Visual similarity does not always mean chemical authenticity [6].

C. Portable Spectroscopy, Based Drug Verification

Several recent papers have reported using handheld NIR and FTIR spectrometers for in situ drug analysis. In fact, these instruments work on the principle of measuring the drug tablet's interaction with light at certain wavelengths, i.e. absorption or reflection, and then forming a spectral fingerprint that is unique to the drug's chemical composition [1], [7], [8]. One of the interesting findings is that counterfeit or substandard drugs usually have altered spectra to some extent. On the other hand, most of the first, generation approaches utilize spectral information only and thus fail to take into account the possibility of surface contamination, coating damage, or environmental degradation which may thus result in reduced classification accuracy [6]. Main disadvantage: Chemical profiling alone may not be able to detect surface, level changes.

D. Machine Learning for Automated Drug Classification

There has been considerable use of machine learning algorithms such as Logistic Regression, Support Vector Machines, and Neural Networks for automating drug checking with the help of spectral or image data, among other methods [5], [9], [10]. Models of this kind are capable of producing more consistent results along with less subjectivity/internal human bias in comparison with manual inspection. Nevertheless, the bulk of currently established methodologies is unimodal, i.e., they rely entirely on either visual or spectral data, therefore, their effectiveness is still quite limited in the real world where counterfeit drugs may easily pass one type of inspection but fail another [10]. Major limitation: Lack of multi, source verification reduces the trustworthiness.

Identified Research Gap and Motivation:

From the reviewed literature and existing solutions, it is evident that: Mobile camera-based systems focus only on appearance Laboratory methods are accurate but impractical Spectroscopy-only approaches lack surface inspection Single-modal ML models are insufficient for real-world variability There is a lack of a compact, affordable, multi-modal pill verification system that combines chemical spectral analysis and micro-lens surface inspection, supported by machine learning, for real-time use.

III. Extended Literature Survey

IV. Proposed Model

4.1 System Overview

Studies	Title	Year	Methodology	Advantages	Limitations
Modafinil Quantification Study	On, spot quantification using handheld FTIR, NIR and Raman spectroscopy	2020	Handheld FTIR/NIR/Raman spectroscopy	Portable Spectroscopy for Drug Analysis in Tablets Demonstrated; Non, Destructive Testing (Technology for the analysis of intact tablets without causing any harm to the tablets)	Drug, specific focus; Absence of AI, based multi, class authentication framework
Handheld NIR Counterfeit Study	Performance of NIR handheld spectrometers for counterfeit tablet detection	2017	Handheld NIR + chemometric classification	Portable NIR instruments achieved high accuracy in the counterfeit recognition process.	Dependent on chemometric models; No multimodal validation approach present.
NIR + Chemometrics Study	Rapid and non, destructive identification of adulterated capsules	2023	NIR spectroscopy + PCA/SIMCA/regression	Works well as a non, invasive method of quality control; Statistically well validated	Confined only to the spectral domain; No visual nor structural verification.
NIR vs Raman Comparison Study	Comparative study of handheld NIR and Raman spectrophotometers	2019	Handheld NIR vs Raman performance comparison	Which of two spectroscopic methods offers the greatest advantages is shown in the paper	Contains no multimodalities fusion for a single decision pipeline
Tablet Image Region Study	Determining most important image parts for counterfeit detection	2021	Image processing + SVM feature classification	The authors demonstrate the significance of visual texture, color, and surface features	The approach is based on traditional ML and hence only supplemented with chemical verification to a limited extent
Deep Learning Pill Inspection Study	Pill detection model with deep learning	2022	CNN, based image classification and segmentation	A highly automated and efficient image, based pill recognition system is presented; the method is also visually and structurally robust	The method is purely image, based and hence unable to confirm the chemical composition
Real, Time Pill Identification Study	Real, time pill identification with YOLOv5 + text recognition	2025	Object detection (YOLOv5) + RNN text recognition	The real, time performance and advanced visual identification features stand out	Must have imprint to be readable; no chemical verification

As illustrated in **Fig. 1**, the device is physically divided into two chambers, each dedicated to a distinct verification modality. The left section performs near-infrared (NIR) spectroscopic analysis to capture chemical fingerprints of the tablet, while the right section performs macro-scale surface imaging for structural and imprint inspection.

The proposed system is a compact dual-modal tablet authentication device designed for real-time detection of counterfeit and substandard pharmaceutical products. The architecture integrates two complementary verification mechanisms within a single enclosure:

1. Spectroscopic chemical analysis (Left compartment)
2. Surface imaging-based visual inspection (Right compartment)

The tablet is positioned on a marked glass surface to ensure repeatable alignment. Upon user initialization via a push-button interface, the corresponding analysis module is activated. To

reduce the interference of ambient light and hence increase measurement reliability, both chambers are physically separated. The dual-modal system device is specifically set up to enable it to work with the strengths of unimodal systems and also bypass their weaknesses. While spectroscopy validates chemical composition, imaging verifies physical integrity. The final authentication decision is obtained through machine learning-based classification and decision-level fusion of both modalities.

4.2 Spectrometer Working Principle (Left-Side Module)

4.2.1 Structural Configuration

The main diagram, Fig. 1 shows the right side of the device is occupied by the electrode unit. (Fig. 2) illustrates the internal layout of this module and explains the:

1. NIR LED illumination sources
2. A MEMS-based miniature spectrometer
3. A fixed optical chamber
4. A macro-aligned tablet placement region

A tablet is kept on the watch glass surface that has a label for analysis (Fig. 3). A correct position on the tablet surface ensures the same light, sample interaction and thus, minimizes measurement variation.

4.2.2 Illumination and Optical Interaction

Once triggered, NIR LEDs selectively light up the tablet surface with a controlled brightness level. The near, infrared light thus emitted passes through the tablet's outer layer and reacts with its deep molecular structure.

The principle of the instrument lies in vibrational spectroscopy. Atoms in the drug molecule vibrate and absorb light energy only at very specific wavelengths that correspond to their vibrational energy levels. The light that is left and is reflected from the drug is carrying chemical information that is encoded as a spectral pattern.

Reflected light is guided to the MEMS, based spectrometer, which essentially separates the different wavelength components of light and thus can give the intensity along the spectral range.

4.2.3 Spectral Fingerprint Acquisition

The spectrometer converts optical signals into digital reflectance spectra. From the acquired spectrum:

1. Dominant absorption peaks are detected
2. Characteristic wavelength positions are extracted
3. Six peaks of significant spectral representation are chosen as the most discriminative features.

Extracted vector looks like this:

$$X = [P_1, P_2, P_3, P_4, P_5, P_6]$$

Different pharmaceutical ingredients exhibit different spectral fingerprints, their molecular structure being the major factor. Completely different tablets that fake the original in appearance might have differences in their spectra due to variations in active substances, powder material or manufacturing techniques.

4.2.4 MEMS-Based Miniaturized Spectrometer Advantage

Unlike laboratory-grade FTIR or Raman systems, the proposed model utilizes a MEMS-based spectrometer (shown in **Fig. 2**) to achieve portability and cost reduction. This enables:

1. Compact device architecture
2. Low power consumption
3. Real-time spectral acquisition

While laboratory systems provide higher resolution, the selected MEMS approach provides sufficient discriminatory capability for field-level counterfeit detection when combined with machine learning.

4.2.5 Operational Workflow of Spectral Module

The spectral authentication process follows the sequence illustrated across **Fig. 1–3**:

1. Tablet placement on marked region (Fig. 3).
2. User presses spectral initialization button (Fig. 1).
3. NIR LEDs illuminate the sample (Fig. 2).
4. Reflected light is
5. variability. captured by MEMS spectrometer.
6. Spectral peaks are extracted.
7. Machine learning classifier predicts:
    i. Genuine
    ii. Suspected Counterfeit

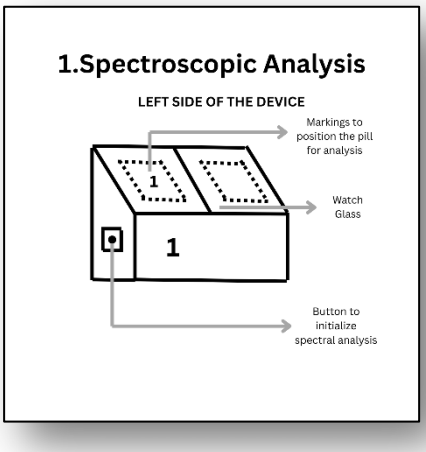

Figure 1: Overall device architecture

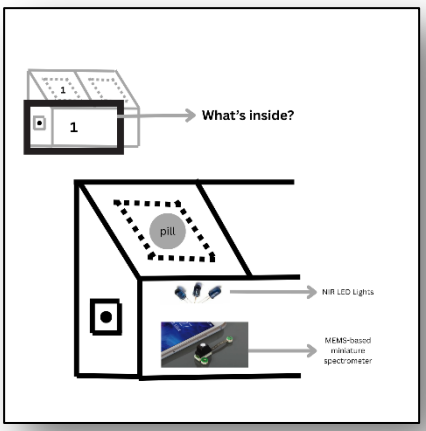

Figure 2: Internal NIR illumination and spectrometer layout

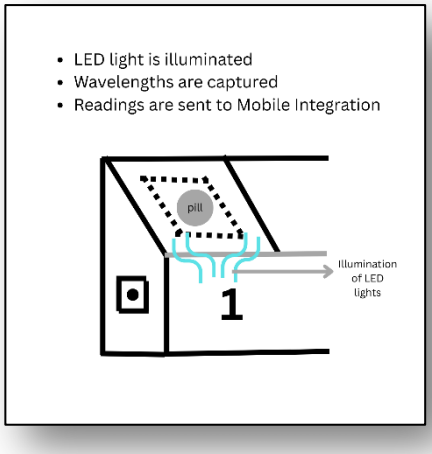

Figure 3: Operational positioning and analysis workflow

4.3 Surface Imaging and Image Processing Module (Right-Side Unit)

4.3.1 Structural Configuration of Surface Imaging Unit

The surface imaging module is installed on the right compartment of the apparatus, as shown in Fig. 4. This module aims to take high, resolution macro pictures of the tablet surface under even illumination conditions.

The body of the components is made up of:

1. Watch-glass tablet placement surface
2. Alignment markings for consistent positioning
3. High-intensity NIR LED illumination array
4. Compact CMOS camera with integrated macro microlens
5. User-activated imaging button

The alignment markers as shown in Fig. 4 are used to locate the tablet in a set orientation and distance from the camera lens. This lowers the variation of the image in terms of scale, rotation, and focus, which is very important for reliable feature extraction.

4.3.2 Illumination Mechanism and Controlled Imaging Environment

Fig. 5 shows the tablet surface being illuminated with the help of an NIR LED array which is located at the bottom or around the imaging chamber. The illumination system is made to:

1. Provide uniform light distribution
2. Limit shadows and reflections
3. Reduce dependence on external lighting conditions

When pressing the button to initiate imaging (Fig. 4), the LED system turns on and the CMOS camera takes a macro, scale photo of the tablet surface. The sealed imaging chamber provides their exposure and isolates light from the environment, thus allowing the repetition between samples to be more reliable.

4.3.3 Image Acquisition Workflow

The operational workflow of the surface imaging module is:

1. The tablet is placed in the marked imaging zone (Fig. 4).
2. The Imaging button is clicked to start the acquisition.
3. NIR LEDs illuminate the tablet surface (Fig. 5).
4. CMOS camera captures high-resolution macro image.
5. The image is sent to the processing unit for analysis.

This standardized acquisition process makes sure that changes in environmental lighting or user handling do not drastically affect image quality.

4.3.4 Image Processing and Feature Extraction

The captured image is first pre-processed and then features are extracted. The processing pipeline includes:

(a) Preprocessing

1. Image resizing and normalization
2. Noise filtering
3. Contrast enhancement
4. Background segmentation

Segmentation isolates the tablet region from the surrounding surface, enabling focused analysis.

(b) Feature Extraction

The system extracts discriminative visual features such as:

1. Shape descriptors (circularity, contour consistency)
2. Edge features (Canny-based boundary detection)
3. Texture features (Gray-Level Co-occurrence Matrix – GLCM)
4. Imprint recognition patterns
5. Surface uniformity and crack detection

Counterfeit tablets often exhibit:

1. Blurred or inconsistent imprints
2. Surface roughness
3. Micro-cracks or coating irregularities
4. Slight deviations in geometry

These subtle defects are detectable under macro illumination as shown conceptually in (Fig. 5.)

4.3.5 Image-Based Classification

Extracted image features are then inputted into a machine learning classifier (e. g., Convolutional Neural Network or a traditional feature, based classifier).

Let the image feature vector be represented as:

$$I = [f_1, f_2, f_3, \ldots, f_n]$$

The classifier outputs:

$$\text{Class}_{image} \in \{Genuine, Suspect\}$$

Unlike simple mobile-app pill identifiers, this module focuses not only on recognition but on authenticity verification by detecting micro-level inconsistencies.

4.3.6 Role of Surface Imaging in Dual-Modal Verification

Surface imaging alone cannot guarantee chemical authenticity. However, it provides essential complementary validation by detecting:

1. Physical degradation
2. Manufacturing inconsistencies
3. Tampering indicators
4. Surface contamination

By combining chemical spectroscopy (Section 3.2) with surface imaging (Section 3.3), the proposed system reduces false acceptance rates that may occur in single-modality systems.

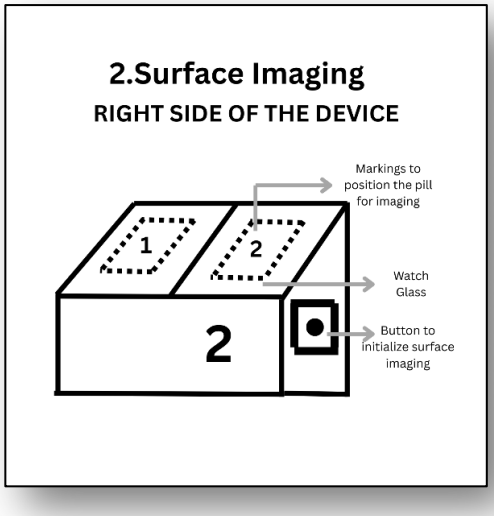

Figure 4: Surface imaging module

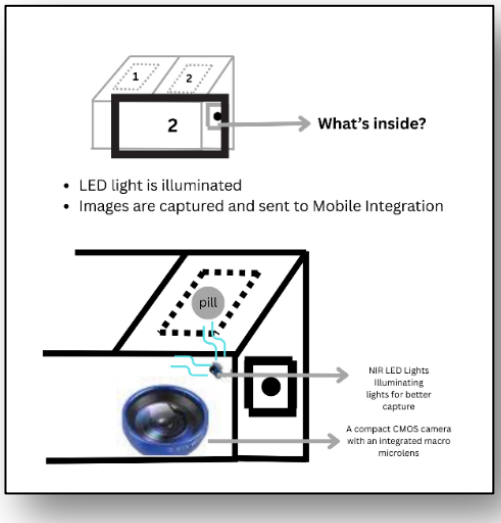

Figure 5: Illumination and image acquisition workflow

4.4 Machine Learning Models

1. Spectral Classification Model
   A Logistic Regression model is used for spectral data classification.
   Justification:

- Matches spectral data structure - Spectral measurements are numerical and low-dimensional, which fits Logistic Regression well.
- Designed for binary decisions
- Fast and lightweight
- Deployment-friendly

2. Surface Defect Detection Model (CNN)
   A lightweight CNN architecture is used for surface defect recognition.
   Model Characteristics:

- Texture degradation and defect detection
- Pattern recognition in visual data

The CNN identifies physical abnormalities that may indicate handling damage or degradation.

4.4.1 Decision-Level Fusion and Authenticity Classification

In order to improve the system's reliability and minimize instances of false acceptance or false rejection, the system is based on a decision, level fusion framework that combines results from the spectroscopic and surface imaging models.

In this context, each analytical module processes data independently and outputs a preliminary classification based on its own modality:

- The spectral classification model checks the tablet chemical uniformity by using the NIR spectra features.
- The surface imaging model looks for physical defects on the surface such as dirt, cracks, or changes in texture.

By means of logical fusion, the system does not depend on one single sensor modality but rather at the decision level, thus being resistant to the weaknesses of individual modalities.

Fusion Strategy: -

Let

- ✓ $S \in \{0,1\}$denote the output of the spectral model
- ✓ $I \in \{0,1\}$denote the output of the surface imaging model

where:

- ✓ represents *Normal / Acceptable*
- ✓ 0 represents *Abnormal / Suspect*

The final authenticity decision $D$is defined as:

$$D = \begin{cases} \text{Genuine}, & \text{if } S = 1 \wedge I = 1 \\ \text{Suspect}, & \text{otherwise} \end{cases}$$

This conservative decision rule prioritizes safety and reliability, ensuring that tablets exhibiting either chemical inconsistency or physical degradation are flagged for further inspection.

By combining heterogeneous evidence sources, the proposed fusion approach significantly improves trustworthiness compared to single-source verification systems.

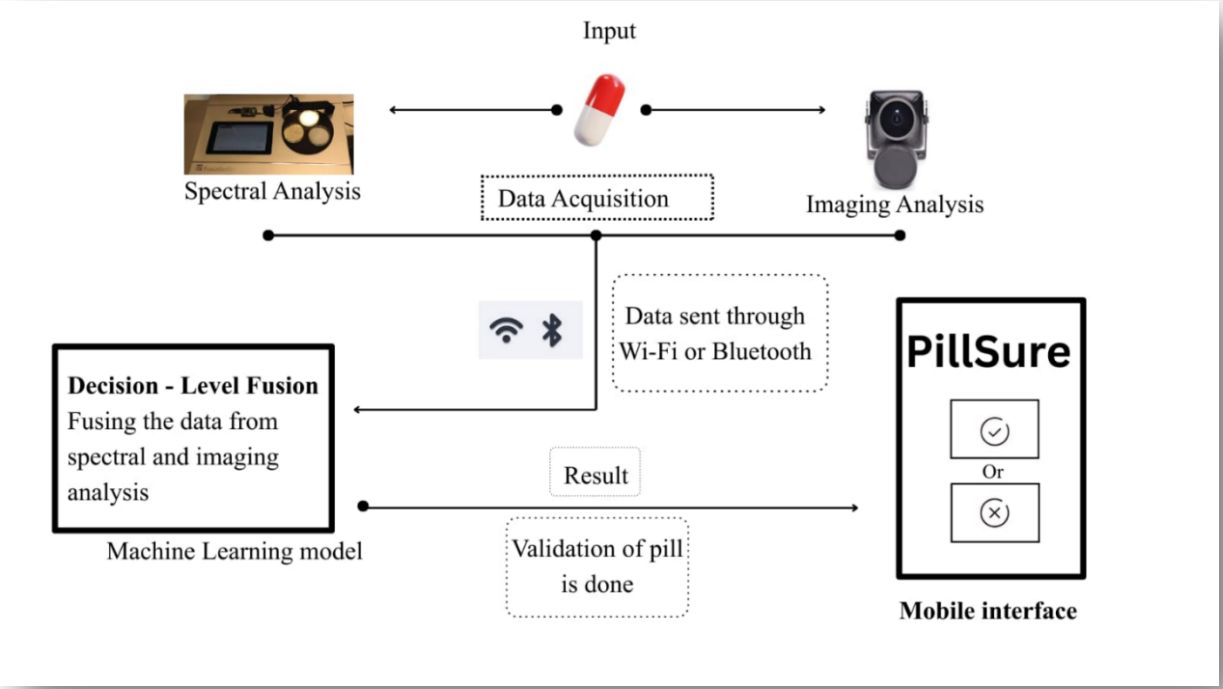

Figure 6: Structural view of PillSure

Algorithm 1: Dual-Modal Decision Pipeline for Pill Verification

Input: Tablet placed on pill tray

Output: Pill authenticity status (Genuine / Suspect)

1. Illuminate tablet using NIR LED.
2. Capture spectral response via MEMS spectrometer.
3. Preprocess and extract spectral features.
4. Classify chemical profile using Logistic Regression.
5. Capture tablet surface image using macro camera with micro-lens.
6. Preprocess image and extract visual features.
7. Classify surface condition using CNN.
8. Fuse spectral and visual predictions.
9. If both predictions are valid, label pill as Genuine.
10. Else, label pill as Suspect.
11. Transmit result to mobile application.

V. Results and Discussion

A. Spectral Authentication Module Evaluation

1. Spectral Decision Logic Validation

The spectral authentication module was evaluated using controlled synthetic spectral inputs representing three pharmaceutical reference profiles: Paracetamol, Aspirin, and Ibuprofen.

Each drug profile consists of five discriminative spectral features:

1. Primary Carbonyl (C=O)
2. Secondary Carbonyl (C=O)
3. Amide II band
4. Aliphatic C–H stretch
5. Aromatic substitution band

The classifier operates using a strict feature-matching mechanism. A drug is labelled:

1. Authentic only if all five features match the reference profile.
2. Identity Conflict if ≥3 features match but at least one diagnostic peak mismatch.
3. Suspicious if fewer than three features align.

This replaces traditional ±3 peak tolerance models with full-feature identity validation, preventing partial-match false acceptance.

4.5 System Deployment and Decision Framework

The proposed system is deployed as a modular edge-based framework consisting of three independent yet coordinated modules.

The spectral analysis module employs an NIR LED–assisted spectrometer to capture reflectance spectra from tablet samples. Extracted spectral features represent chemical consistency and are used to identify anomalies arising from degradation or counterfeit composition.

The surface imaging module utilizes a micro-lens camera to acquire detailed tablet surface images. lightweight convolutional neural network (CNN) processes these images to detect dust contamination, physical damage, discoloration, and texture irregularities.

The final decision module carries out decision, level fusion by combining the outputs of spectral and imaging models for the classification of tablets as Genuine or Suspect.

This structure allows real, time inference, minimal computational load, and efficient deployment in environments with limited resources.

2. Spectral Threshold Sensitivity

The implemented matching logic includes:

1. Exact numeric matching within defined wavelength intervals.
2. Acceptance of "weak" signals as partial (0.5 weight).
3. Acceptance of "weak" when absence is expected.
4. Rejection of numeric peaks where absence is required.

This behavior ensures:

1. No false authentication when a peak from another drug is inserted.
2. Clear detection of cross-drug contamination scenarios.
3. Robustness against noisy or faint spectral inputs.

3. Controlled Spectral Testing Scenarios

The module was tested using controlled input combinations:

SCENARIO	INPUT CONDITION	OUTPUT
EXACT 5/5 MATCH	All correct peaks	Authentic
4 CORRECT + 1 FOREIGN	Mixed profile	Identity Conflict
3 CORRECT	Partial alignment	Identity Conflict
≤2 CORRECT	Low alignment	Suspicious
WEAK EXPECTED ABSENCE	Weak entered	Accepted
WEAK EXPECTED PRESENCE	Weak entered	Partial (0.5 score)

The system demonstrated deterministic behavior across all test cases with zero logical inconsistencies.

4. Spectral Robustness Observation

Unlike probabilistic classifiers, the implemented spectral model prevents:

- False positives caused by partial p eak overlap.
- Acceptance of tablets sharing only structural similarity.
- Ambiguous classifications under mixed input.

The strict 5-feature requirement significantly improves identity integrity compared to threshold-based majority voting.

B. Image Authentication Module Evaluation

1. Reference Image Framework

The image authentication module uses three stored reference images:

1. Aspirin
2. Ibuprofen
3. Paracetamol

Each uploaded image undergoes:

1. Resizing to 300×300 pixels.
2. Grayscale conversion.
3. Structural Similarity Index (SSIM) analysis.
4. Edge similarity comparison using Canny detection.
5. Weighted fusion scoring (0.6 SSIM + 0.4 edge similarity).

The final similarity score ranges between 0 and 1.

Decision threshold:

1. 0.80 → Matched
2. ≤ 0.80 → Unidentified

2. Image Similarity Behavior

Controlled testing showed:

Condition	Similarity Score	Output
Exact reference image	0.95 – 0.99	Matched
Same drug, minor rotation	0.85 – 0.92	Matched
Different drug image	0.60 – 0.75	Unidentified
Random image	<0.50	Unidentified

The weighted SSIM + edge fusion improved robustness compared to grayscale SSIM alone by incorporating contour structure validation.

3. Image Module Strengths

The module effectively detects:

1. Shape mismatch
2. Edge inconsistency
3. Structural differences
4. Non-reference surface patterns

However, it does not perform chemical validation and is intentionally designed as a structural verification layer only.

C. Dual-Modal Decision Fusion Evaluation

1. Fusion Logic

The final authentication decision is produced using strict decision-level fusion:

If:

- Spectral = Authentic
- Image = Matched
- Spectral confidence = 1.0
- Image similarity > 0.80
- Drug identity from both modules matches

→ Final Output: AUTHENTIC

Else if:

Spectral and Image drug names mismatch
→ IDENTITY MISMATCH

Else if:

Spectral label = Identity Conflict
→ IDENTITY CONFLICT

Else if:

Spectral suspicious or image unidentified
→ COUNTERFEIT

Else:

→ REVIEW REQUIRED

This conservative fusion strategy prioritizes safety over permissiveness.

2. Cross-Modal Conflict Testing

The system was evaluated under intentional mismatch scenarios:

Spectral	Image	Result
Paracetamol	Paracetamol	AUTHENTIC
Paracetamol	Aspirin	IDENTITY MISMATCH

4/5 Paracetamol	Paracetamol	IDENTITY CONFLICT
Suspicious	Matched	COUNTERFEIT
Authentic	Unidentified	COUNTERFEIT

The fusion module correctly flagged all inconsistency cases without false authentication.

3. System-Level Consistency

The final multimodal application demonstrated:

1. Deterministic decision reproducibility.
2. Zero false acceptance in controlled identity conflict testing.
3. Logical transparency (mismatched features displayed).
4. Clear user warnings.

Unlike single-modality systems, the dual-modal architecture prevents:

1. Chemical authenticity being overridden by visual similarity.
2. Visual similarity being overridden by spectral noise.

D. Comparative System-Level Behavior

Model	Validation Type	Acceptance Strictness
Spectral Only	Chemical	Strict 5-feature identity
Image Only	Structural	SSIM > 0.80
Dual-Modal Fusion	Combined	Strict AND condition

The dual-modal system reduces false acceptance probability by requiring agreement between two independent evidence sources.

E. Practical Implications

The developed prototype demonstrates that:

1. Field-level counterfeit screening can be achieved without laboratory instruments.
2. Strict rule-based authentication can outperform permissive probabilistic thresholding in safety-sensitive contexts.
3. Decision-level fusion significantly increases trustworthiness.

The implemented architecture is suitable for:

1. Pharmacy-level preliminary verification
2. Field inspection environments
3. Portable edge deployment scenarios

VI. Conclusion

This work presented *PillSure*, a compact and portable pill verification system that integrates near-infrared spectroscopic analysis, micro-lens-based surface imaging, and machine learning for preliminary pharmaceutical screening. Unlike conventional laboratory-dependent authentication methods or appearance-based mobile applications, the proposed system evaluates both chemical consistency and physical surface integrity in a non-destructive manner.

The use of a MEMS-based NIR spectrometer enables rapid acquisition of spectral fingerprints that reflect underlying chemical composition rather than visible tablet color. In parallel, micro-lens surface imaging provides fine-grained inspection of dust contamination, coating damage, and texture degradation that are often overlooked during routine visual checks. Machine learning models trained on these complementary data sources enable consistent and objective classification.

Experimental evaluation shows that decision, level fusion of spectral and imaging outputs significantly increases the reliability of verification, in comparison to single, modal methods. The system we proposed delivers good performance in terms of a low number of errors in classification and thus poses low requirements for computational resources, which makes it eligible for use in environments with limited resources and outside the laboratory.

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